

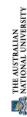
Probabilistic Data Generation for Deduplication and Data Linkage

Peter Christen

Data Mining Group, Australian National University
Contact: peter.christen@anu.edu.au

Project web page: <http://datamining.anu.edu.au/linkage.html>

Funded by the ANU, the NSW Department of Health,
and the Australian Research Council (ARC) (LP #0453463)



Peter Christen, July 2005 – p.1/13

Data linkage and deduplication

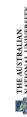
- The task of linking together records representing the same entity from one or more data sources (patient, customer, business, etc.)
- Real world data is *dirty*, so cleaning and standardisation is important
- Applications of data linkage
 - Remove duplicates in a data set (internal linkage)
 - Merge new records into a larger master data set
 - Create customer or patient oriented statistics
 - Compile data for longitudinal studies
 - Geocode data (match addresses with geographic reference data)



Peter Christen, July 2005 – p.3/13

Test data for data linkage

- Various data sets are used in recent publications (*restaurant*, *cora*, *citeSeer*, *census*, etc.)
- Usually very small (less than 2,000 records)
- Proprietary and even confidential data has been used
- There is a lack of standard test data
- Hard to compare new algorithms and to learn how to use and customise data linkage systems
- Recent small repository: *RIDDLE*
<http://www.cs.utexas.edu/users/ml/riddle/>
(Repository of Information on Duplicate Detection, Record Linkage, and Identity Uncertainty)



Peter Christen, July 2005 – p.5/13

A probabilistic data set generator

- First data generator by *Hernandez & Stolfo* (1996)
- Improved by *Bertolazzi et.al.* (2003)
(no details given, not publicly available)
- Our generator
 - Open source (Python)
 - Part of the *Febrl* data linkage system
(Free extensible biomedical record linkage)
 - Easy to modify and improve by a user
 - Based on real world frequency look-up tables for names, addresses, date of birth, etc.
 - Includes look-up tables with real typographical errors

- Data linkage and deduplication
- Data linkage techniques
 - Artificial data
 - Probabilistic data set generator
 - Example data generated
 - Experimental study
 - Conclusions and outlook

Peter Christen, July 2005 – p.2/13

Data linkage techniques

- Computer assisted linkage goes back to 1950s
- Deterministic linkage
 - Exact linkage (if a unique identifier of high quality – precise, robust, stable over time – is available)
 - Rules based linkage (complex to build and maintain)
- Probabilistic linkage (*Fellegi & Sunter*, 1969)
 - Apply linkage using available (personal) information (which can be missing, wrong, coded differently, or out-of-date)
- Modern approaches
 - Based on machine learning, data mining, or information retrieval techniques (clustering, decision trees, active learning, learnable string metrics, graphical models, etc.)

Peter Christen, July 2005 – p.3/13

Artificial data

- Privacy issues prohibit publication of real data (for example of names, addresses, dates of birth, etc.)
- De-identified or encrypted data cannot be used (as linkage algorithms work on name and address strings)
- Artificial data as alternative to real data
 - Based on real data (frequency and misspellings tables)
 - Must model content and statistical properties of real data
- Advantages
 - Content and error modifications can be controlled
 - Data can be published
 - Easy to repeat and verify experiments

Peter Christen, July 2005 – p.6/13

Data generation

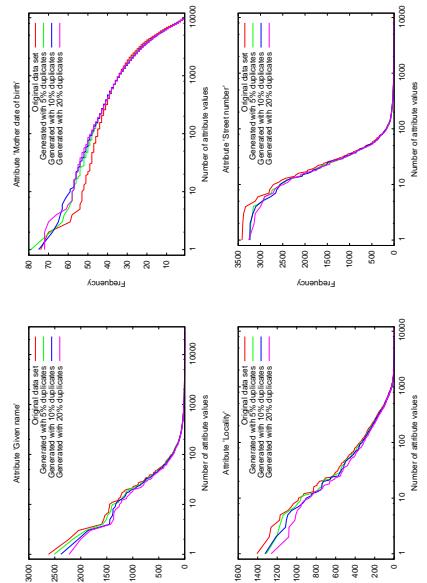
- Step 1: Create original records
 - Randomly select values from various frequency look-up tables, or from a user specified range (e.g. for date of birth)
- Step 2: Create duplicates based on original records by introducing modifications
 - Single errors (insert, delete, substitute a character; transpose two characters)
 - Insert or delete a whitespace (split or merge a word)
 - Set to missing (empty string), or insert new value
 - Swap with another value from a look-up table
 - Swap two attribute values (e.g. given name ↔ surname)

Data set with 4 original and 6 duplicate records

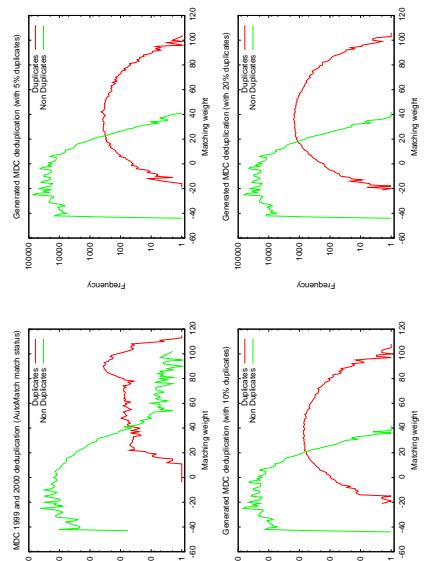
REC_ID	ADDRESS1	ADDRESS2	SUBURB
rec-0-org,	willy place,	pine ret villa,	taree
rec-0-dup-0,	willyplace,	pine ret villa,	taree
rec-0-dup-1,	pine ret villa,	willy place,	taree
rec-0-dup-2,	willy place,	pine ret villa,	taree
rec-0-dup-3,	willy parade,	pine ret villa,	taree
rec-1-org,	stuart street,	hartford,	menton
rec-2-org,	griffith street,	mross,	kilda
rec-2-dup-0,	griffith street,	myross,	kilda
rec-2-dup-1,	ellenborough place,	mycross,	sydney
rec-3-org,	ellenborough place,	kalkite homestead,	

- Each record is given a unique identifier, which allows the evaluation of accuracy and error rates

Sorted attribute frequencies



Deduplication matching weights



Peter Christen, July 2005 – p. 10/13

THE AUSTRALIAN NATIONAL UNIVERSITY

Peter Christen, May 2005 – p.13/13

THE AUSTRALIAN NATIONAL UNIVERSITY

Peter Christen, July 2005 – p. 10/13

Conclusions and outlook

Several possible improvements

- Relax independence assumption (based on real world frequency tables), for example a change of address results in new street name, number and type, as well as postcode and locality

- Allow generation of groups of records, for example for households (census)

- Fine tune error modifications (scanning, typing, etc.)

- Do further comparison studies with real data sets

- See project web page for more information

<http://datamining.anu.edu.au/linkage.html>

THE AUSTRALIAN NATIONAL UNIVERSITY

Peter Christen, July 2005 – p. 11/13

Peter Christen, July 2005 – p. 12/13

Peter Christen, July 2005 – p. 13/13